PROCEEDINGS

55. IWK

Internationales Wissenschaftliches Kolloquium
International Scientific Colloquium

13 - 17 September 2010

Crossing Borders within the ABC

Automation,

Biomedical Engineering and

Computer Science

Faculty of
Computer Science and Automation

www.tu-ilmenau.de

TECHNISCHE UNIVERSITÄT
ILMENAU

Impressum
Published by

Publisher:	Rector of the Ilmenau University of Technology Univ.-Prof. Dr. rer. nat. habil. Dr. h. c. Prof. h. c. Peter Scharff
Editor:	Marketing Department (Phone: +49 3677 69-2520) Andrea Schneider (conferences@tu-ilmenau.de) Faculty of Computer Science and Automation (Phone: +49 3677 69-2860) Univ.-Prof. Dr.-Ing. habil. Jens Haueisen
Editorial Deadline:	20. August 2010
Implementation:	Ilmenau University of Technology Felix Böckelmann Philipp Schmidt

USB-Flash-Version.

Publishing House:	Verlag ISLE, Betriebsstätte des ISLE e.V. Werner-von-Siemens-Str. 16 98693 Ilmenau
Production:	CDA Datenträger Albrechts GmbH, 98529 Suhl/Albrechts
Order trough:	Marketing Department (+49 3677 69-2520) Andrea Schneider (conferences@tu-ilmenau.de)

ISBN: 978-3-938843-53-6 (USB-Flash Version)

Online-Version:

Publisher:	Universitätsbibliothek Ilmenau ilmedia Postfach 10 05 65 98684 Ilmenau

Home / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=16739

THE RECURSIVE ICA, A NEW RECURSIVE APPROACH FOR SEPARATING ONE SIGNAL SOURCE FROM DOMINANT NOISE.

D. Trommer, R. Baumgart-Schmitt, M. Krautwald, C. Walther, C. Menz

University of Applied Sciences Schmalkalden, Faculty of Electrical Engineering

ABSTRACT

In this approach a signal extraction algorithm for bioelectrical signals measured by a sensor array under low signal noise ratio will be conducted.

A well known approach for blind source separation of a linear mixture of signals, which will be measured by a sensor array, is the Independent Component Analysis (ICA). We propose that the ICA can separate a single source from noise. Therefore the quality of a downstream classification can be improved.

By using several known derivates of ICA, the processing time depends on the dimensions of the mixture space and often no information about previous computations can be used to improve accuracy or processing time.

In this new approach we have implemented a fixed-point ICA algorithm in a recursive way. The main idea consists of using the predicted mixing matrix which is calculated by a certain number of mixing matrices computed before.

By using our new approach the processing speed can be improved with comparable performances.

Furthermore the approach can adapt on different conditions of input data sets. That means the robustness can be improved.

Index Terms - ICA, sensor array, preprocessing, biomedical

1. INTRODUCTION

Signal extraction is an important part of a classification process. In this paper a new recursive approach will be introduced.

Most of the classification algorithm, e.g. artificial neural networks (ANN) or Support Vector machines (SVM), need a signal extraction preprocessing algorithm with sufficient quality. The classification quality can be improved by signal extraction with high signal noise ratio.

With internal error-detection methods the classification algorithm can classify data sets as unidentified or identified. In our approach we are using the method of independent component analysis (ICA) to solve the signal extraction task and separate the source-signal from noise and artifacts and using the feedback of the downstream classification algorithm to check for a suitable solution.

The Independent Component Analysis is a computational method for separating statistical dependent datasets into statistical independent ones. In special cases, discussed in the following, the ICA can solve the problem of blind source separation (BSS). The problem of BSS consists of recovering a set of unobservable source signals from observed mixtures of the sources.

In contrast to correlation based algorithm like principal component analysis (PCA) the ICA uses higher order statistical moments like the kurtosis [1].

The algorithm we are introducing is based on the FastICA-Algorithm [2]. With a given multidimensional vector $\underline{x}$, ICA means a transformation into a defined transformation space so that the components are as statistical independent between each other as possible. This is called Minimal Mutual Information and is one of the broadest definitions of the ICA.

A special case will be found, if the vector $\underline{x}$ is a result of an invertible transformation of a random variable. In this case the ICA can solve the problem of blind source separation.

2. ICA

Mathematically, the observed random vector $\underline{x} \in C^M$ is assumed to be generated according to the instantaneous linear mixing model

$$\underline{x} = \underline{A}\underline{s} + \underline{n}, \tag{1}$$

where the source vector $\underline{s} = [s1, s2,\ldots,s_N] \in C^N$ is made of unknown mutually independent components. The mixing matrix $\underline{A} \in C^{MxN}$ is also unknown. The noise vector $\underline{n}$ is only assumed to be statistically independent of the sources.

The FastICA [2, 4] algorithm is perhaps the most popular method for ICA, due to its simplicity, convergence speed and satisfactory results in numerous applications. The one source separating algorithm with cubic or hyperbolic-tangency nonlinearity, related to the optimization of the kurtosis contrast under prewhitening, offers global convergence if the ICA model is fulfilled and the sample size tends to infinity [2, 4].

2.1. FastICA

The FastICA algorithm, as mentioned before, is a fixed point algorithm for ICA. The algorithm is a pseudo online or batch processing method, where a fixed number of before collected sample (block) of data were processed at once. For that the Newton–Raphson method is used. As a measure of nongaussianity the negentropy will be used. It is a fast approach by approximating the negentropy

$$J(\underline{z}) \propto [E\{G(\underline{z})\} - E\{G(\nu)\}]^2, \qquad (2)$$

with vector $\underline{z}$ as whitened observed data, ν as a Gaussian variable of zero mean and unity variance, G a nonquadratic contrast function (as in 2.2) and E as Eigenmatrix.

The FastICA algorithm can be defined in the following way:

1. Center the data to make its mean zero.
2. Whiten the data to give $\underline{z}$.
3. Choose an initial (e.g., random) matrix $\underline{W}$ of unit norm.
4. Let $\underline{W}^+ \leftarrow E\{\underline{z}g(\underline{W}^T\underline{z})\}-E\{g'(\underline{W}^T\underline{z})\}\underline{W}$, where g is defined, e.g., as in 2.1.2
5. Let $\underline{W} \leftarrow \underline{W}^+/\|\underline{W}^+\|$.
6. If not converged, go back to step 4.

The FastICA algorithm finds a unity unmixing matrix $\underline{W}=\underline{A}^{-1}$, such that the projection $\underline{W}^T\underline{z}$ maximizes nongaussianity [3, 5].

2.2. contrast function

In the originally FastICA approach some contrast function were introduced and also some rules for chosing them were formulated [4].
The contrast functions are formulated

$$G_1(\underline{z}) = \frac{1}{a_1}\log(\cosh(a_1\underline{z})), \qquad (3)$$

$$G_2(\underline{z}) = -\frac{1}{a_2}\exp(-a_2 \cdot \underline{z}^2/2), \qquad (4)$$

$$G_3(\underline{z}) = \frac{1}{4}\ \underline{z}^4, \qquad (5)$$

where $1 \leq a_1 \leq 2$, $a_2 \approx 1$ are constants and $\underline{z}$ is a vector of real or complex data.

The following benefits of these contrast functions were summarized:

• G_1 is a good general-purpose contrast function.

• When the independent components are highly super-Gaussian, or when robustness is very important, G_2 may be better.

• If computational overhead must be reduced, piecewise linear approximations of G_1 and G_2 may be used.

• using kurtosis, or G_3, is justified on statistical grounds only for estimating sub-Gaussian independent components when there are no outliers.

According to this benefits or differences between the contrast function it can be assumed that the choice of the correct contrast function is necessary for qualitative extraction of the sources.

2.3. Problems of FastICA

The FastICA algorithm has some disadvantages among processing speed and robustness.

1. Preprocessing procedures may take most of the processing time of the algorithm.
2. Robustness against changing environment or mixing matrices
3. No feedback from former calculated blocks are available

3. IMPLEMENTATION OF A NEW ADAPTIVE RECURSIVE ICA ALGORTIHM

3.1. Calculate preprocessing procedures in parallel mode to the ICA-process

To solve the problem of Blind Source Separation the ICA must have some preprocessing procedures as a requirement. The data has to be whitened, centered and also a covariance matrix has to be calculated. To improve the speed of the ICA we calculate the preprocessing procedures of the block_n while the block_{n-1} is in calculation by the ICA.

3.2. Recursive processing and initial $\underline{W}$ feedback

One disadvantage of the Newton- Raphson method, as it is used in the FastICA, is that it is not convergating well if the start point is far from the solution. In real environments the mixing matrix will change fluently. First we assume that the change of the mixing matrix $\underline{A}$ take place in small values. That's why we implement a recursive feedback of the calculated unmixing matrix $\underline{W}$ to avoid this problem.

To check that we have found a suitable solution the downstream classification algorithm gives a feedback to the ICA algorithm, whether the extracted signal can be identified by known values of features. The given $\underline{W}$ will be used as initial value for the ICA algorithm, so the accuracy for extracting the same independent component can be improved. The results of the calculations of signal mean square error (SMSE) between standard FastICA algorithm and the recursive and adaptive implementation (RA-ICA) is shown in figure 1. For that a set of artificial signals were mixed with a fluently changing mixing matrix A. The value of the mixing matrix A is illustrated by the rotation angle of the unmixing matrix W, the SMSE between one original signal source and the estimated signal sources were calculated. The number of iterations is limited to three. For FastICA algorithm the same initial W were used for each calculation. The contrast independent SMSE [5, 6, 7] is defined by

$$SMSE = E\{|\underline{s} - \underline{s}'|^2\}, \tag{6}$$

with s as original source vector and s' as the estimated source vector. E means the estimation of the mean error.

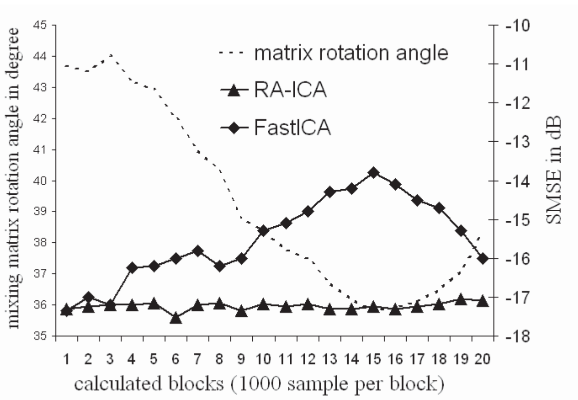

Figure 1 SMSE of FastICA against RA-ICA, initial value of FastICA is marked as arrow.

In figure 1 we can see that, the SMSE of the FastICA is strongly dependent on the initial value of the matrix W. By using our approach the initial value of W will be near the solution in each iteration. It should be mentioned that the convergence of our algorithm can not be assumed if the angle of the matrix W is not changing in small steps.

3.3. Prediction of rotation the mixing matrix

As mentioned in 3.2 the variation of the mixing matrix has to bee small. This might be a problem, because in real environment the value of the variation is not limited and can increase immediately. Therefore we are using a simple prediction method of the weighted moving average (WMA) [8].

The WMA at time t is defined by

$$WMA_t = \frac{\sum_{z=1}^{n} r_z \cdot V(t-(z-1))}{n}, \tag{7}$$

with r_z the factor of value V(t-(z-1)) and n is the number of used former values. This WMA will be calculated after each processed block and by

$$\underline{W}_{pred} = \nu \cdot WMA + \underline{W}_{old}, \tag{8}$$

where $\underline{W}_{pred}$ is the prediction of the unmixing matrix W, $\underline{W}_{old}$ is the processed W of the former block and ν as a weighting factor $0 \leq \nu \leq 1$, we are getting a predicted value of W. Whith n=5 we are using the results of the last five blocks.

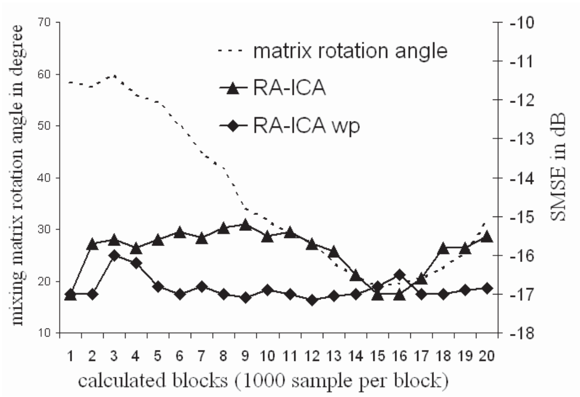

Figure 2 SMSE of RA-ICA against RA-ICA with prediction of W(pw)

In figure 2 the results of calculating the SMSE of RA-ICA with prediction of W and without prediction of W are shown. A dataset of artificial signals and random noise are mixed with a fluently changing mixing matrix. In this case we are using a five times steeper gradient as used for calculation in 3.2. Again the number of iterations is limited to three. In figure 2 an effective improvement can be seen. That means the improvement of implementing a prediction is shown.

4. RESULTS

The usage of separating artificial single sources was demonstrated in chapter 3. To check the usability for real data sets with dominant noise the following experiments with a SoundCheck© audio-test-system where conducted.

As a signal source we have used a signal generator with a 1 kHz sinus output (Sinus) plugged onto an active speaker. Another active speaker is used as noise generator.

Another experiment will be done by playing a mono- speech- sound file (Audio) over the signal speaker and again dominant noise through the other speaker.

The length of each source signal is about one minute, so that there are more or equal 60 blocks per calculation. The mixing matrix of the signals is slightly variable like in 3.2.

Four microphones were used for parallel audio recording. For each experiment the SMSE between the estimated source signal and the real source signal were calculated over the whole signal length. The results shown in figure 4 are the calculated SMSE from 50 different calculations.

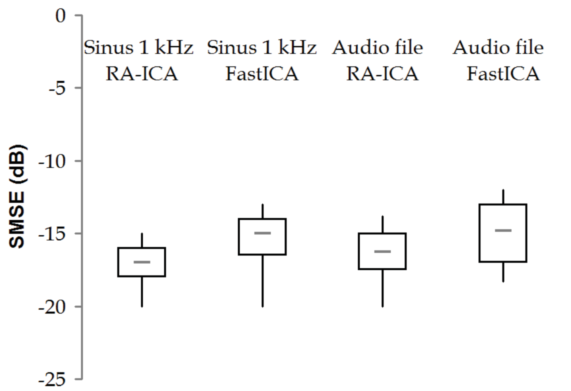

Figure 3 Experimental results (SMSE) of 50 calculations in real environment see figure 3. (The value of the termination parameter of the Newton-Raphson method is 0,5x10^{-6})

Method	Signal	Iterations [mean]±[std]	Block processing time [ms]
RA-ICA	Sinus	3 ± 1	247
FastICA	Sinus	6 ± 5	611
RA-ICA	Audio	4 ± 3	300
FastICA	Audio	6 ± 6	680

Table 1 Experimental results (average number of iterations and average block processing time) of 50 calculations in real environment see figure 4.

As it can be interpreted from figure 3, that the results of RA-ICA algorithm are not significant different to the results of the FastICA algorithm if the number of iterations is not limited and the value of the mixing matrix is changing. Table 1 shows that the RA-ICA is faster than the FastICA. The speed was improved by saving a number of iteration and the preprocessing time.

5. CONCLUSION

The FastICA algorithm was adapted. The robustness against changing environment, the classification quality and the processing speed were improved.

Therefore the new version of the algorithm can be formulated as followed.

5.1. The RA-ICA Algorithm

Data will be whitened, get zero mean to give $\underline{z}$ in parallel mode to the former ICA calculation.

1. Calculate $\underline{W} = \nu \cdot WMA + \underline{W}_{old}$,

2. Let $\underline{W}^{+} \leftarrow E\{\underline{z}g(\underline{W}^{T}\underline{z})\}-E\{g'(\underline{W}^{T}\underline{z})\}\underline{W}$, where g is defined, e.g., as in 2.1.2

3. Let $\underline{W} \leftarrow \underline{W}^{+}/\|\underline{W}^{+}\|$.

4. If not converged, go back to step 2.

5. Check if solution is the right source (downstream classification feedback) if not go back to step 1 using a random $\underline{W}$.

6. For calculating next step take the next data block and the resulting $\underline{W}$, go back to 1.

5.2. Future research

In the future research an adaptive contrast function should be implemented for improving robustness against different signal types. Also the algorithm should be implemented on an embedded processing unit for signal extraction and signal-separating from artefact for bioelectrical signals.

6. REFERENCES

[1] F.J. Theis, “Mathematics in Independent Component Analysis”, Dissertation, University of Regensburg, 2002

[2] A. Hyvärinen and E. Oja, “A fast fixed-point algorithm for independent component analysis,” *Neural Comput.*, vol. 9, no. 7, pp. 1483–1492, Oct. 1997.

[3] S. C. Douglas, “On the convergence behavior of the FastICA algorithm,” in *Proc. 4th Int. Symp. Ind. Compon. Anal. Blind Signal Separat.*, Nara, Japan, Apr. 1–4, 2003, pp. 409–414.

[4] A. Hyvärinen, J. Karhunen, E. Oja, “Independent Component Analysis”, John Wiley & Sons, pp. 170-200, 2001

[5] V. Zarzoso and P. Comon, "Robust Independent Component Analysis by Iterative Maximization of the Kurtosis Contrast with Algebraic Optimal Step Size", IEEE Transactions on Neural Networks, Vol. 21, No. 2, February 2010, pp. 248-261.

[6] V. Zarzoso and P. Comon, "Comparative Speed Analysis of FastICA", in: Proceedings ICA-2007, 7th International Conference on Independent Component Analysis and Signal Separation, London, UK, September 9-12, 2007, pp. 293-300

[7] V. Zarzoso, P. Comon and M. Kallel, "How Fast is FastICA?", in: Proceedings EUSIPCO-2006, XIV European Signal Processing Conference, Florence, Italy, September 4-8, 2006

[8] Ya-lun Chou, “Statistical Analysis”, Holt International, section 17.9, 1975